Chest-Lead Generation with Single-Lead

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Abstract

The three main ECG measurement methods are resting ECG, Holter monitoring, and treadmill method. Wearable devices have been developed that could measure long-term ECG signals daily. The aim of this study is to synthesize chest lead ECGs from a single-lead ECG using a generative adversarial network (GAN). Lead I was used as input data of our model. For generator U-net model was implemented and for the discriminator patch discriminator was used. Our model was trained with two independent datasets which are China dataset and PTB-XL dataset both open data from Physionet. For evaluation methods fréchet distance (FD) score and mean squared error (MSE) were used. Low FD and MSE score validate the similarity between generated and reference signal. Mean FD score and MSE score of the model trained with China dataset were 13.757 and 0.042, respectively. Mean FD score and MSE score of the PTB-XL dataset were 11.321 and 0.038. Despite the vector difference of lead I and chest leads the FD score and MSE score were low. Novelty of or proposed methods are that chest leads are generated by lead I which can be easily obtained from wrist. Proposed method can overcome the limitations of modern ECG measurements. Low FD and MSE scores indicate the possibility that the proposed method can be applied to wearable devices and obtain ECG signals measured from the chest.

1. Introduction

An electrocardiogram measures the rhythm and activity of the heart. Standard ECG measurement are limb-lead and chest-lead measurements. Lead I, II, III, aVR, aVL, and aVF represents the limb-leads and V1, V2, V3, V4, V5, and V6 represents the chest-leads. Each lead measures each different vector of the heart.

Unlike conventional methods, ECG is measured by variety of devices such as smartwatches. The difference between conventional method of ECG measurement is mainly ability of obtaining information and complexity of obtaining ECG signal. Wearable devices' limitations are lack of information. Therefore, to overcome these limitations, ECG lead conversion has been widely studied.

Proposed method synthesizes chest lead from lead I to overcome the limits of single lead measurement methods.

2. Methods

Two independent databases were used to train our model. U-net generator and patch discriminator was used to build GAN. Two datasets validated one another to see how well model was trained. Figure 1 depicts the overview of our proposed method.

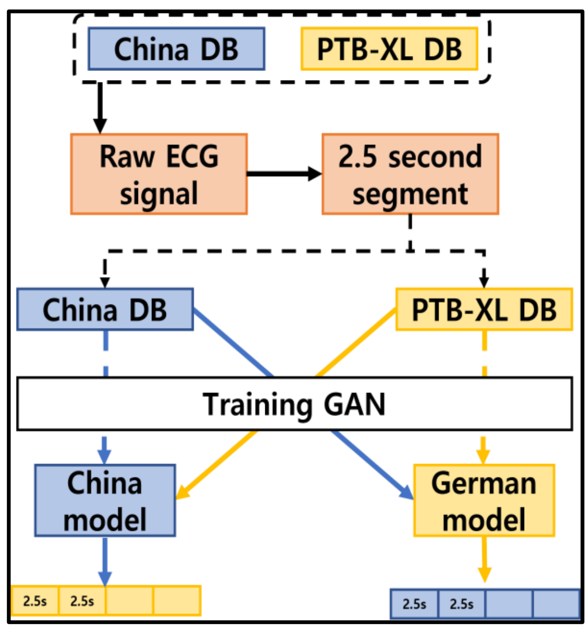

Figure 1. Model overview of proposed method.

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2.1. Datasets and Preprocessing

PTB-XL [1] and China datasets [2], were used to train our model which are available on PhysioNet. PTB-XL and China dataset contains 21,837 records and 10,646 records respectively. Both database's sampling rate are 500Hz and the duration of each record was 10 seconds. Each record was segmented to 2.5s resulting 87,348 and 42,584 segments for the PTB-XL and China datasets.

2.2. Model description

The discriminator depicted in Figure 2 classifies each N patch in a signal as real or fake. N is smaller than the full-size signal. The advantage of PatchGAN it can be implemented to long signal with fewer parameters. [3] [4] The discriminator contains five convolution layers with batch normalization and Leaky ReLU. A slope of 0.2 for all Leaky ReLU functions, a kernel size of four, and a stride length of two were used. The learning rate was set to 0.0005 for the generator and 0.0001 for the discriminator. In addition, batch size was set as 32. A total of 6 models were trained for generating chest leads.

The waveform of each lead is similar. Moreover, there are two to four beats in a 2.5 s ECG signal. Therefore, the generator in this study is composed of U-net based encoder-decoder. The U-net generator is depicted in Figure 3. To avoid the bottleneck skipped connection, all channels were concatenated at corresponding layers [5]. The encoder part consisted of four residual blocks with convolution layers. Batch normalization and ReLU were used except for the first layer. The decoder consisted of four up convolutions. The last layer of the decoder part, ReLU was used as an activation function. The learning rate was 0.005 and batch size was 32; the kernel size and stride length were 4 and 2, respectively.

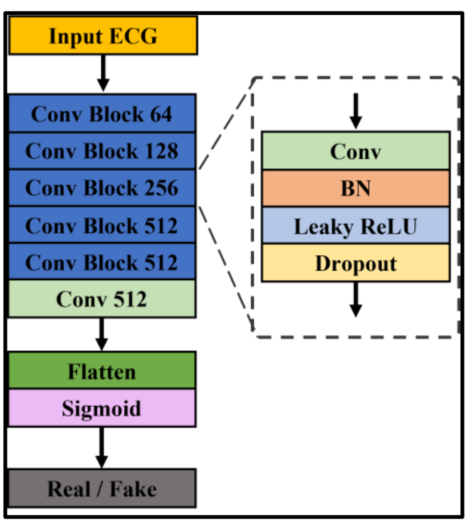

Figure 2. Discriminator architecture.

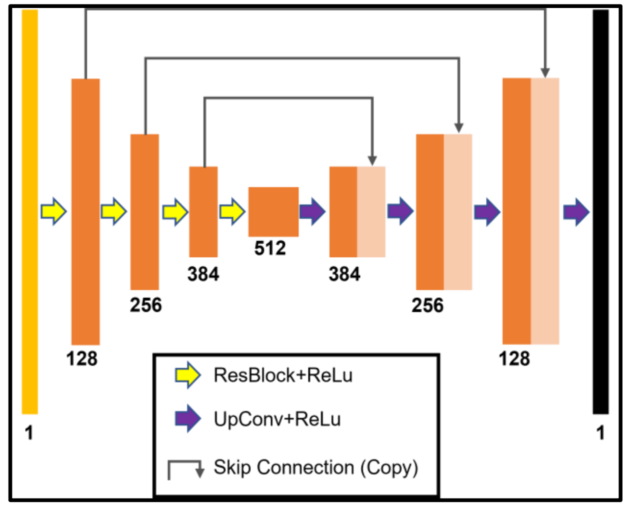

Figure 3. U-net generator architecture.

2.3. Model evaluation

Mean squared error score were calculated to evaluate U-net model. The mean squared error measures the average of squared difference between the predicted state label (X) and reference label (Y) as shown in (1).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2 \quad (1)$$

Moreover, FD score were calculated to see the similarity between generated and reference signal.

3. Results

Generated results trained with PTB-XL and China dataset are presented in this section. Figure 4 shows the generated chest leads from lead I. Left side of the figure are real ECG signals fo V series and right side of the figure are generated signals.

FD and MSE score are listed in Table 1. Lower FD score and MSE score are highlighted as bold. Mean FD score and MSE score of the model trained with China dataset were 13.757 and 0.042, respectively. Mean FD score and MSE score of the PTB-XL dataset were 11.321 and 0.038. The result of evaluation score was slightly lower with the PTB-XL dataset. Evaluation score of V1 and V2 were lower than other V series.

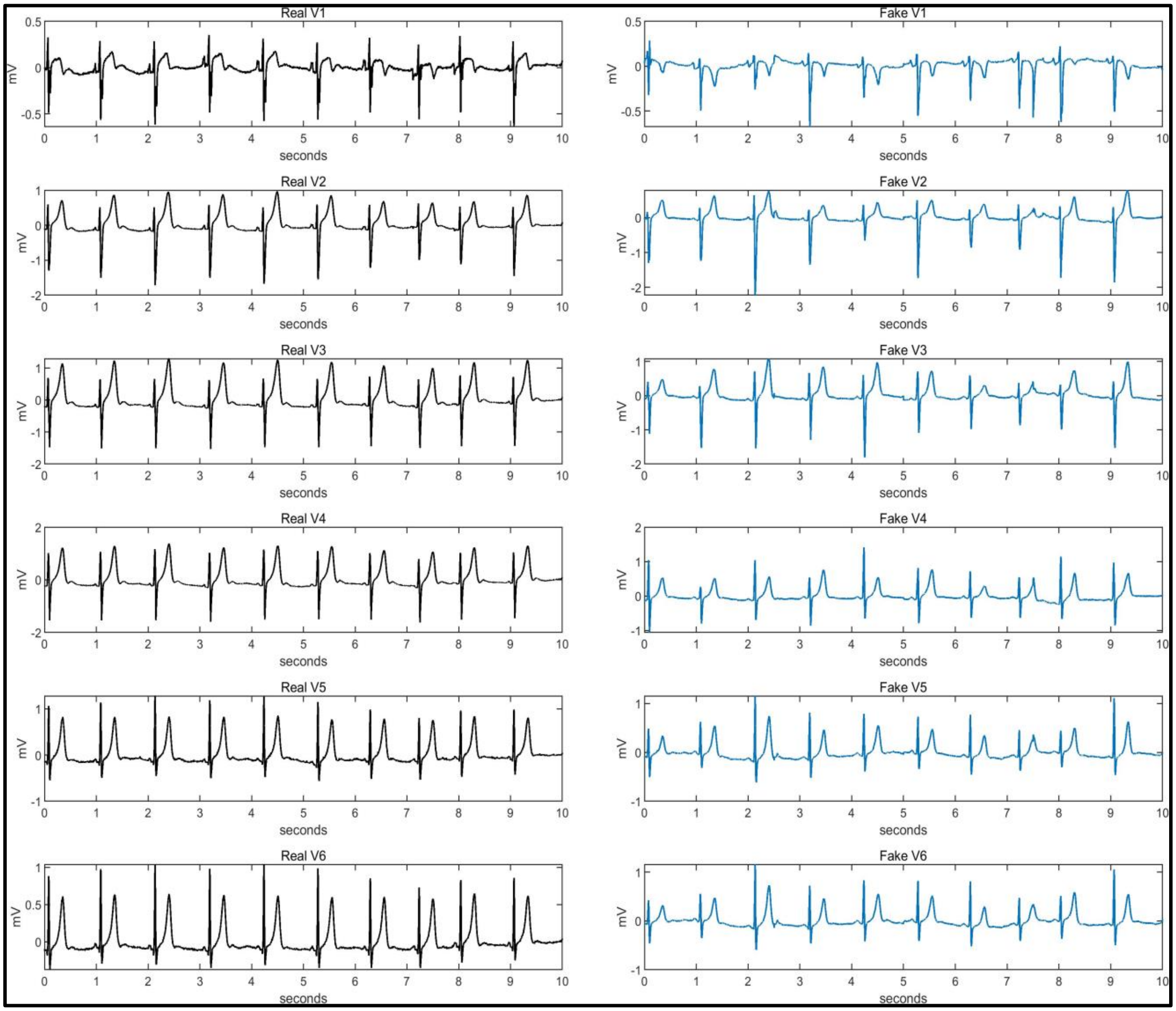

Figure 4. Left side of the signal with black lines are reference chest lead ECG and right side of the figure with blue lines are generated chest lead ECG.

Table 1. FD score and MSE score results

	China database		PTB-XL database	
	FD	MSE	FD	MSE
V1	13.637	0.029	**6.101**	**0.021**
V2	10.847	0.058	**10.837**	**0.050**
V3	17.639	0.058	**10.128**	**0.051**
V4	15.265	0.046	**12.581**	**0.043**
V5	**13.602**	**0.033**	15.931	0.034
V6	**11.550**	**0.028**	12.347	0.026
Mean	13.757	0.042	**11.321**	**0.038**

4. Discussion

We have proposed a method of generating chest leads from limb lead. Despite the vector difference of chest lead and limb lead conversion of ECG signal from limb lead I to V series was successful. As illustrated in Figure 4. not all V series were generated exactly compared to the reference signal. However, the R-peak time position were generated at the same position corresponding to the reference signal.

There were several limits to our study. First, both PTB-XL and China dataset were mixture of normal and abnormal ECG signals. Therefore, resulted high FD score and MSE score. Models could not learn abnormal signals due to lack of data. Secondly, the difference in amplitude of generated signal and reference signals were seen causing high evaluation score. Lastly, artifacts such as baseline wandering, and noise signal effected the evaluation score. However, most of the generated signals did not show baseline wandering as the reference signal.

In the future work we will train our model with balanced data by combining multiple datasets to prevent overfitting. Moreover, generating abnormal signals will be tested and evaluated. Lastly, evaluation methods other than FD score and MSE score will be implemented to confirm if the generated ECG signals are capable of diagnostic purpose.

Acknowledgments

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